Automatic Coil Compression for Parallel MRI based on Noise Variance Estimation

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Purpose: Coil compression[1-3] methods combine parallel MRI data from large coil arrays into few virtual coils, and therefore significantly speed up the reconstruction. Coil compression is usually achieved by singular value decomposition, where the number of virtual coils can be determined by thresholding the singular values. However, the thresholds have to be manually tuned for different datasets or coil geometries. Here, a new approach based on noise variance estimation is proposed to automatically select the number of virtual coils. The noise variance is used to determine the virtual coils in which signals are mostly noise and can therefore be disposed of. We apply the proposed method with Geometric-decomposition Coil Compression (GCC)[1] and validate it on various datasets from different coil geometries.

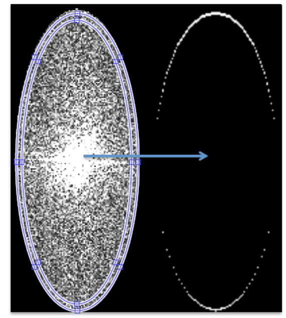

Fig. 1: Getting the noisy region when corner-cut sampling was performed.

Methods: The edge of k-space usually contains limited signal and is dominated by noise. This algorithm is based on estimating the proportion of k-space variance that is due to these noisy outer k-space regions. A Fourier Transform is taken in the readout dimension to convert k-space data into hybrid space, where each readout location (x) is considered a "slice". The center 20 slices are considered when determining the number of virtual coils. For corner-cut sampling patterns, a region very close to the edge of the oval in the k_y-k_z plane is used as the noisy region (Fig.1). Otherwise, a one-pixel edge of k-space is used instead. For each slice, two sets of vectors are formed: v_i contains all sampled data points in the noisy region for the i^{th} coil and u_i contains all sampled points in the slice. Then, the noise proportion for slice r (σ_r) is calculated as the sum of the variances in v_i divided by the sum of the variances in u_i, i.e. $\sigma_r = \frac{\sum_{i=1}^{n} Var(v_i)}{\sum_{i=1}^{n} Var(u_i)}$. For coil compression, we aim to retain $1-\sigma_r$ of the total k-space variance. For each slice, the sampled multi-coil data points are reformatted into a matrix and singular value decomposition is performed on this matrix.[1-2] The singular values are then squared and normalized so that each entry represents the proportion of k-space variance explained by the corresponding singular vectors. Next, the squared and normalized singular values are added up until surpassing the threshold value $1-\sigma_r$ found above. For slice r, the number of singular values required to achieve this is the recommended number of virtual coils. The maximum of these counts across all considered slices is set to be the ideal number of virtual coils.

Data set	n recommended coils			
	$R_y = R_z = 1$	$R_y = 2$, $R_z = 1$	$R_y = 1$, $R_z = 2$	$R_y = R_z = 2$
Brain 2D 160x220x8	4	4	4	5
Body 3D 192x224x92x32	6	6	6	7
Brain 3D 100x100x70x32	6	6	7	7

Table 1: Recommended numbers of virtual coils (no under-sampling, under-sampling in y, under-sampling in z, under-sampling in both).

Results: The algorithm was tested on a 2D dataset (for which Single Coil Compression (SCC) was performed on the only available slice) and on two 3D datasets, presenting different coil geometries. Each dataset was tested on fully sampled, under-sampled by a factor of two in y and z separately and then under-sampled by a factor of two in both dimensions. 20 auto-calibration lines were kept in all cases. Table 1 shows automatically determined number of virtual coils for each case. The results are consistent for different acceleration factors and suggest levels of compression that closely match the kinks in the corresponding nRMSE plots (Fig. 2) and the numbers of coils found empirically. Figure 2 shows a compressed slice for each of the datasets, the slice constructed using all coils, and the absolute error (x20). The image quality is very similar before and after coil compression, but the reconstruction time is significantly shorter (e.g. 260s vs. 1620s for body 3D). Furthermore, the coil compression algorithm runtime is much shorter than the full reconstruction time (less than 2.5% of full runtime for body 3D). Therefore, time considerations for the algorithm can be neglected.

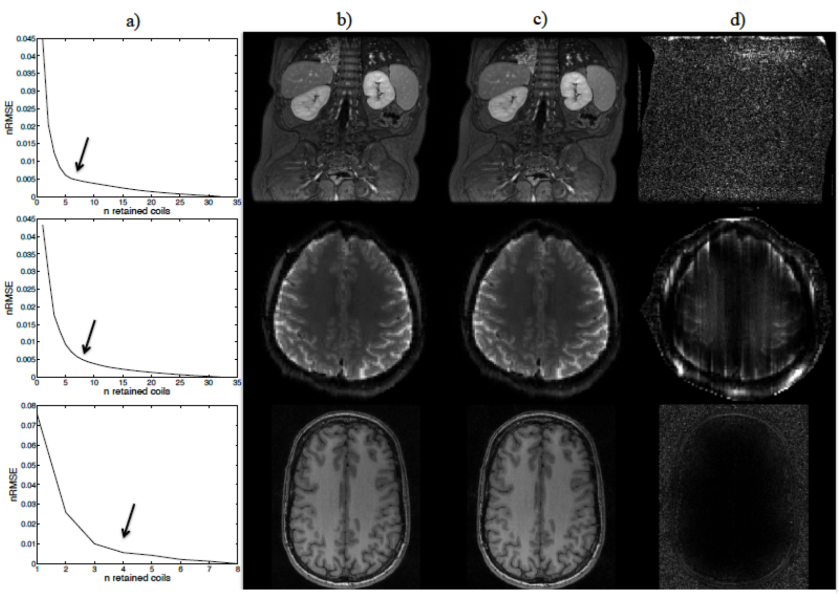

Fig. 2: From left to right: a) nRMSE plot for sum of squares images using different numbers of retained coils, b) slice using all coils, c) slice using recommended number of coils, d) difference image times 20. Top to bottom: Body 3D (192x224x92x32), Brain 3D (100x100x70x32), Brain 2D (160x220x8).

Discussion: The proposed method effectively determines a compression level that is appropriate for each dataset considered. Masking out a noisy region can be generally applied to all sampling patterns and acceleration factors. At the same time, if a pre-scan noise acquisition is available, the noise variance can be estimated directly and then be used for the proposed algorithm.

Conclusion: An automatic coil compression method has been proposed and validated on the different datasets. The proposed noise variance metric is robust for different sampling patterns and acceleration factors.

References: [1] T Zhang, et al. MRM 2013; 69: 571–582. [2] F Huang, et al. MRI 2008; 26: 133–141. [3] M Buehrer, et al. MRM 2007; 57: 1131–1139.